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Pattern Classifier for Health Monitoring of Helicopter Gearboxes

Hsinyung Chin and Kouroch Danai
University of Massachusetts
Amherst, Massachusetts

and

David G. Lewicki
Propulsion Directorate
U.S. Army Aviation Systems Command
Lewis Research Center
Cleveland, Ohio

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PATTERN CLASSIFIER FOR HEALTH MONITORING OF HELICOPTER GEARBOXES[1]

Hsinyung Chin, Graduate Research Assistant
Kouresh Danai, Assistant Professor
Department of Mechanical Engineering
University of Massachusetts
Amherst, MA 01003

and

David G. Lewicki
U.S. Army Research Laboratory
Vehicle Propulsion Directorate
NASA Lewis Research Center
Cleveland, OH 44135

Abstract: The application of a newly developed diagnostic method to a helicopter gearbox is demonstrated. This method is a pattern classifier which uses a *multi-valued influence matrix (MVIM)* as its diagnostic model. The method benefits from a fast learning algorithm, based on error feedback, that enables it to estimate gearbox health from a small set of measurement-fault data. The MVIM method can also assess the diagnosability of the system and variability of the fault signatures as the basis to improve fault signatures. This method was tested on vibration signals reflecting various faults in an OH-58A main rotor transmission gearbox. The vibration signals were then digitized and processed by a vibration signal analyzer to enhance and extract various features of the vibration data. The parameters obtained from this analyzer were utilized to train and test the performance of the MVIM method in both detection and diagnosis. The results indicate that the MVIM method provided excellent detection results when the full range of faults effects on the measurements were included in training, and it had a correct diagnostic rate of 95% when the faults were included in training.

Key Words: Detection; diagnosis; helicopter gearbox; pattern classification; vibration signal processing

Introduction: Helicopter drive trains are significant contributors to both maintenance cost and flight safety incidents. Drive trains comprise almost 30% of maintenance costs and 16% of mechanically related malfunctions that often result in the loss of aircraft [6]. As such, it is crucial that faults be detected and diagnosed in-flight so as to prevent loss of lives.

Fault diagnosis of helicopter gearboxes is based primarily on vibration monitoring and extraction of features that relate to individual gearbox components. Therefore, considerable effort has been directed toward the development of signal processing techniques which can quantify such features through the parameters they estimate (e.g., [13,15]). For example, the crest factor of vibration, which represents

[1]This paper is extracted from References [4] and [5]

the peak-to-rms ratio of vibration, has been shown to increase with localized faults such as tooth cracks [1]. However, due to the complexity of helicopter gearboxes and the interaction between their various components, the individual parameters estimated from vibration measurements do not provide a reliable basis for fault detection and diagnosis.

As an alternative to single-parameter based diagnosis, fault signatures can be established so as to consist of many parameters. For this purpose, pattern classification techniques need to be employed [9,14]. Among the various pattern classifiers used for diagnosis, artificial neural nets are the most notable due to their nonparametric nature (i.e., independence of the probabilistic structure of the system), and their ability to generate complex decision regions [16]. However, neural nets generally require extensive training to develop the decision regions. In cases such as helicopter gearboxes, where adequate data may not available for training, neural nets may produce false alarms, undetected faults, and/or misdiagnoses.

In this paper we demonstrate the application of a diagnostic method that can estimate gearbox health based on a small set of measured vibration data. This method uses nonparametric pattern classification in its model, so like artificial neural nets, is independent of the probabilistic structure of the system. Moreover, it utilizes a ***multi-valued influence matrix (MVIM)*** as its diagnostic model that provides indices for diagnosability of the process and variability of the fault signatures [8]. These indices are used as feedback to improve fault signatures through adaptation [7].

To test this method, vibration signals were collected at NASA Lewis Research Center as part of a joint NASA/Navy/Army Advanced Lubricants Program to reflect the effect of various faults in an OH-58A main rotor transmission gearbox. In order to identify the effect of faults on the vibration data, the vibration signals obtained from five tests were digitized and processed by a vibration signal analyzer. The parameters obtained from this signal analyzer were then utilized to train the MVIM method and test its performance in both detection and diagnosis.

MVIM Method:

Measurements are processed in the MVIM method as illustrated in Fig. 1: They are usually pre-processed first to obtain a vector of processed measurements $\mathbf{P}$, then they are converted to binary numbers through a flagging operation (i.e., abnormal measurements characterized by 1 and normal ones by 0) to obtain a vector of flagged measurements $\mathbf{Y}$, and finally they are analyzed through the diagnostic model to produce fault vector $\hat{\mathbf{X}}$. The MVIM method is explained in detail in [3] and [7], and its overall concept is briefly discussed here for completeness.

Fault Signature Representation:

Fault signatures in the MVIM method are represented by the n unit-length columns $\bar{\mathbf{V}}_j \in \mathcal{R}^m$ of a multi-valued influence matrix (MVIM) $\bar{\mathbf{A}}$:

$$\bar{\mathbf{A}} = [\bar{\mathbf{V}}_1 \ \dots \ \bar{\mathbf{V}}_j \ \dots \ \bar{\mathbf{V}}_n] \tag{1}$$

where m denotes the number of characteristic parameters processed from the raw

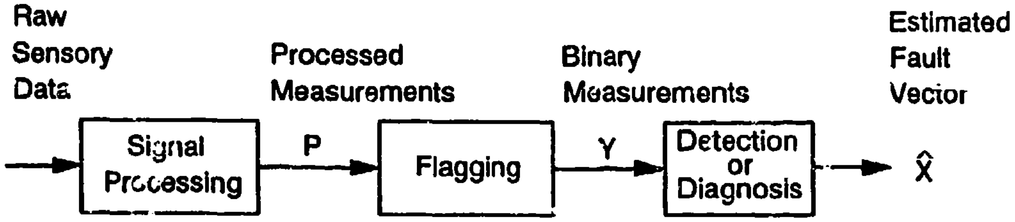

Figure 1: Processing of measurements in the MVIM method.

data, and n represents the number of different fault conditions, including the no-fault condition.

Diagnostic Reasoning: In the MVIM method, the fault vector $\hat{\mathbf{X}}$ which ranks the faults according to their possibility of occurrence is defined by the closeness of the influence vector to the vector of flagged measurements $\mathbf{Y}$ (see Fig. 2).

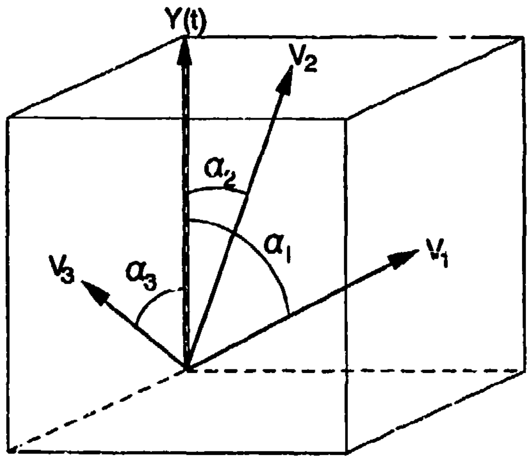

Figure 2: Schematic of diagnostic reasoning in the MVIM method, illustrated in three dimensional space.

Fault Signature Evaluation: The influence vectors defined in Eq. (1) are not known *a-priori* and need to be estimated. In the MVIM method, the error in diagnosis is used as the basis to estimate/update the influence vectors. For this purpose, the fault signatures are updated recursively after the occurrence of each fault to minimize the sum of the squared diagnostic error associated with that fault [8].

One of the unique features of the MVIM method is its ability to evaluate quantitatively the uniqueness of the fault signatures as well as their variability, so that these quantitative measures can be used to improve the flagging operation. In the MVIM method, the uniqueness of fault signatures is characterized by the closeness of pairs of influence vectors. For this purpose, a diagnosability matrix is defined

to represent the closeness of the orientation of individual influence vectors [8], and the index of diagnosability is defined as the smallest off-diagonal component of this matrix so as to denote the closest pair of fault signatures.

In the MVIM method, the variability of fault signatures is defined by their variance. For this purpose, the variance matrix associated with $\bar{\mathbf{A}}$ is estimated to provide a measure of the variations of individual components of the influence matrix. Since in the MVIM method the components of $\bar{\mathbf{A}}$ are adjusted recursively, the variance matrix can be readily estimated during training [7]. The index of fault signature variability in the MVIM method is defined as the largest component of a variance matrix which represents the variability in the components of matrix $\bar{\mathbf{A}}$.

Flagging Unit: The influence matrix $\bar{\mathbf{A}}$ is estimated based on the values of the flagged measurement vector $\mathbf{Y}$. Thus, before the influence matrix is used for diagnostic reasoning, the integrity of the flagging operation needs to be ensured. Ideally, the measurements should be flagged such that no false alarms are produced, all faults are detected, the fault signatures are as spread out as possible, and the variability of flagged measurements for individual faults is minimized. To this end, a Flagging Unit is designed so that it can be tuned to achieve the above goals. The Flagging Unit is tuned iteratively based on a training batch, where at the end of each iteration the total number of false alarms and undetected faults are counted and the uniqueness and variability of the fault signatures are obtained from MVIM. This information is then used as feedback in the next iteration to improve the performance of the Flagging Unit (see Fig. 3). Training stops when the total number of false alarms and undetected faults are minimized, and the uniqueness and repeatability of fault signatures are enhanced [7].

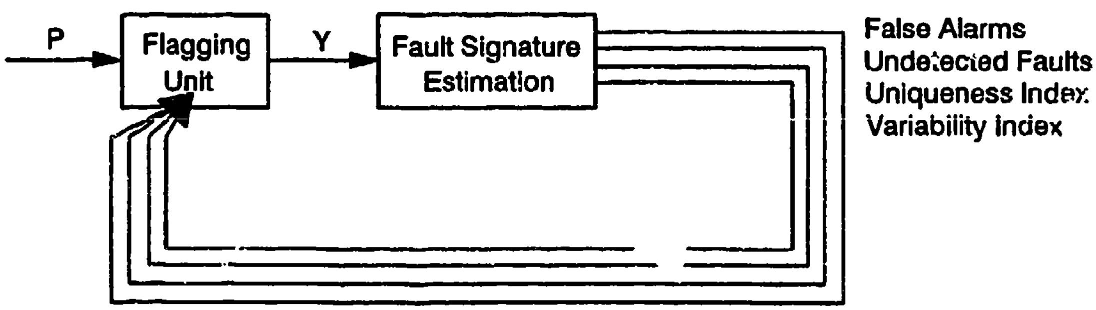

Figure 3: Iterative tuning of the Flagging Unit based on feedback from its diagnostic model.

Experimental: Vibration data was collected at NASA Lewis Research Center to reflect the effect of various faults in an OH-58A main rotor transmission gearbox [11]. The gearbox was tested in the NASA Lewis 500-hp helicopter transmission test stand providing an input torque level of about 3100 in-lbs and an input speed of 6060 rpm. The configuration of the gearbox is shown in Fig. 4. The vibration signals were measured by eight piezoelectric accelerometers (frequency

range of up to 10 kHz), and an FM tape recorder was used to record the signals periodically once every hour, for about one to two minutes per recording (at the tape speed of 30 in/sec, providing a bandwidth of 20 kHz). Two chip detectors were also mounted inside the gearbox to detect the debris caused by component failures The location and orientation of the accelerometers are shown in Fig. 5.

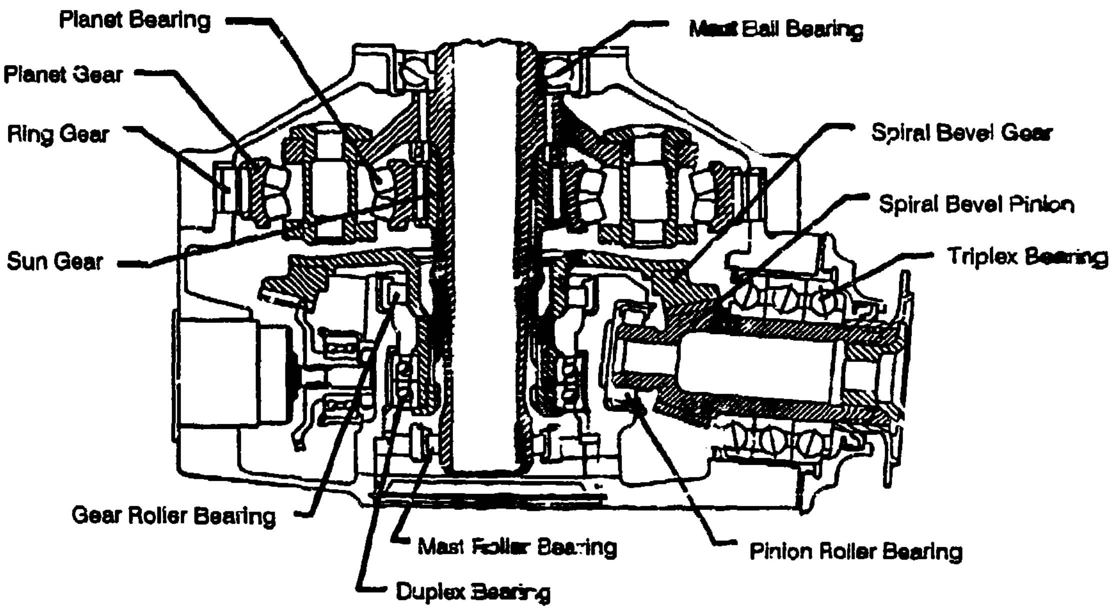

Figure 4: Configuration of the OH-58A main rotor transmission gearbox.

During the experiments, the gearbox was disassembled/checked periodically or when one of the chip detectors indicated a failure. A total of five tests were performed, where each test was run between nine to fifteen days for approximately four to eight hours a day. Among the eight failures which occurred during these tests, there were three cases of planet bearing failure, three cases of sun gear failure, two cases of top housing cover crack, and one case each of spiral bevel pinion, mast bearing, and planet gear failure (see Table 1). Insofar as fault detection during these tests, the chip detectors were reliable in detecting failures in which a significant amount of debris was generated, such as the planet bearing failures and one sun gear failure. The remaining failures were detected during routine disassembly and inspection.

Signal Processing: In order to identify the effect of faults on the vibration data, the vibration signals obtained from the five tests were digitized and processed by a commercially available signal analyzer [17]. For analysis purposes, only one data record per day was used for each test. These data records were taken at the beginning of the day unless a fault was reported, which in that case, the record taken right before the fault incident was selected to ensure that the data record

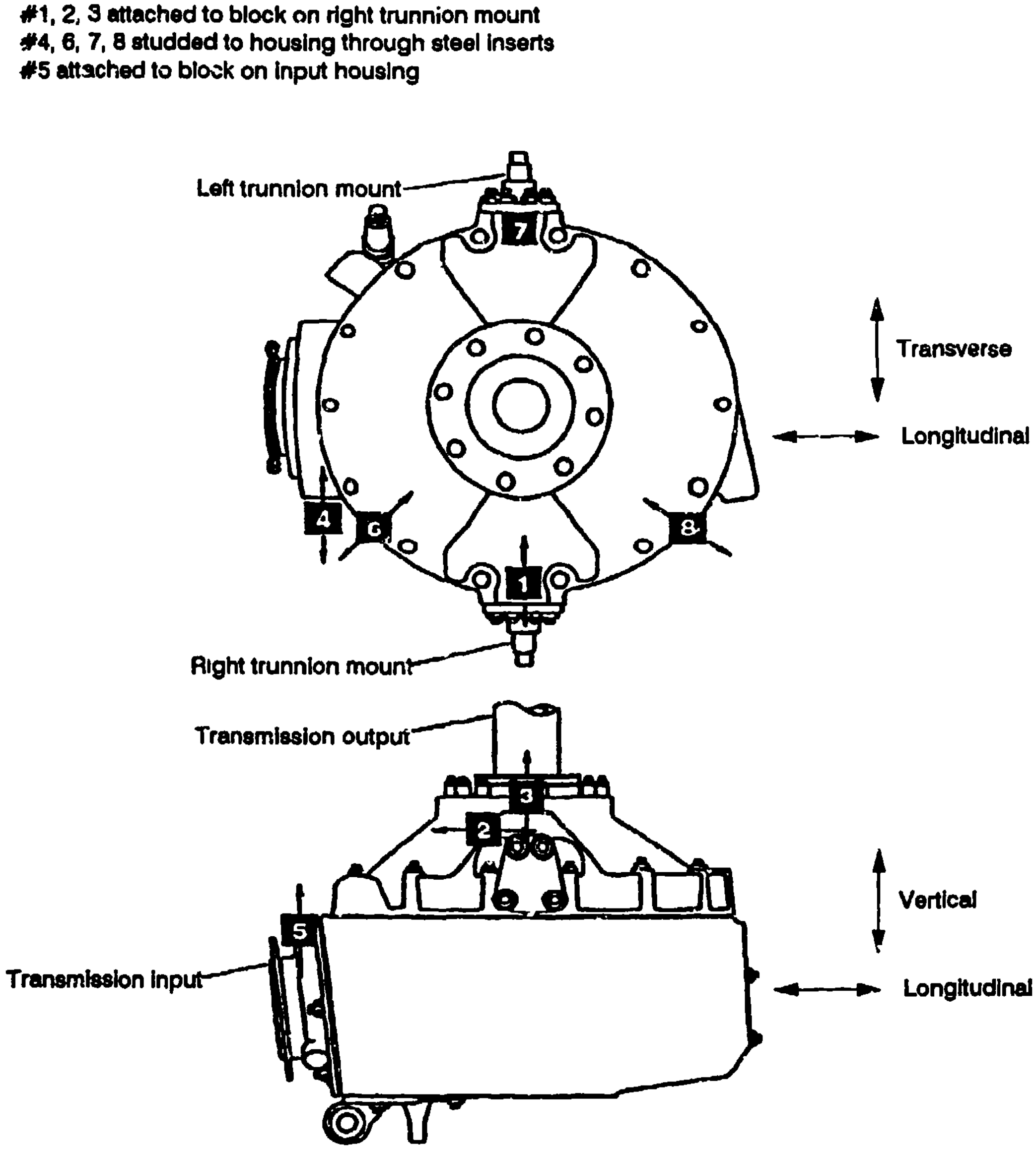

Figure 5: Location of the accelerometers on the test stand.

reflected the fault. Also, in order to reduce estimation errors, each data record was partitioned into sixteen segments and parameters were estimated for each segment and averaged over these segments. A total of fifty-four parameters were obtained, of which nineteen parameters were obtained for statistical analysis, baseband power spectrum analysis, and bearing analysis. The other thirty-five parameters reflected the various features of signal averaged data (seven parameters for each of the five gears) [2].

Implementation: As explained earlier, the MVIM method requires a set of measurements during normal operation and at fault incidents to estimate the no-fault and fault signatures. The parameters obtained from the signal analyzer were utilized to evaluate the performance of the MVIM method, first in detection and then in diagnosis.

Test #	Number of Days	Failures
1	9	Sun gear tooth spall Spiral bevel pinion scoring/heavy wear
2	9	None
3	13	Planet bearing inner race spall Top cover housing crack Planet bearing inner race spall Micropitting on mast bearing
4	15	Planet bearing inner race spall Sun gear tooth pit
5	11	Sun gear teeth spalls Planet gear tooth spall Top housing cover crack

Table 1: Faults occurred during the experiments

Fault Detection: The mean values of the nineteen "non-signal averaged" parameters were used as the components of the measurement vector **P** (see Fig. 1) to train and test the MVIM method in detection. Since signal averaging is usually time consuming and may not be suitable for on-line detection [12], the thirty-five "signal averaged" parameters were not utilized for detection. For scaling purposes, each parameter value was normalized with respect to the value of the parameter on the first day of each test. Since in the experiments the exact time of fault was not known, the exact times for the fault incidents of the five tests needed to be established before the measurements could be used for training and testing the MVIM. For this purpose, *Kohonen's feature mapping* [10], an unsupervised learning algorithm, was first used to classify individual parameters into no-fault and fault cases. The exact time of fault incidents was then established through correlating these parameters with the faults which had been detected in each test [2]. The status of various faults during the five tests are shown in Table 2.

The effectiveness of the MVIM method in detection was evaluated with various training sets. For this purpose, training sets were formed based on parameters from various combinations of the five tests (see Table 3). The MVIM was tested, however, based on the parameters from all of the five tests. For each training case, the MVIM was iteratively trained until perfect detection was achieved within the training set (i.e., no false alarm or undetected fault was found in the training set). Note that the MVIM trained for detection contains only two columns, one representing the no-fault signature and the other representing the fault signature. The detection results produced by the MVIM for eighteen different cases of training are shown in Table 3. For comparison, the results obtained from the MVIM method are contrasted against the results obtained from a multilayer neural net which was trained and tested under the same conditions. Performance of these detection

Day	Fault Status				
	Test #1	Test #2	Test #3	Test #4	Test #5
1	x_0	x_0	x_0	x_0	x_0
2	x_0	x_0	x_0	x_0	x_0
3	x_0	x_0	x_2	x_0	x_0
4	x_0	x_0	x_2	x_0	x_0
5	x_4	x_0	x_0	x_0	x_0
6	x_4	x_0	x_0	x_0	x_0
7	x_4	x_0	x_0	x_0	x_3
8	x_4	x_0	x_0	x_0	x_3
9	x_4, x_1	x_0	x_3	x_0	x_3
10			x_0	x_0	x_3, x_1
11			x_2	x_2	x_3, x_1, x_5
12			x_2	x_2	
13			x_6	x_0	
14				x_1	
15				x_1	

Table 2: Association of data from each day of the five tests with no-fault and various fault cases. The no-fault case is denoted as x_0 and the six faults are represented as x_1: sun gear failure, x_2: planet bearing failure, x_3: housing crack, x_4: spiral bevel pinion failure, x_5: planet gear failure, x_6: mast bearing failure.

methods are represented by the total number of false alarms and undetected faults they produced during testing (denoted as "Total Test Errors" in Table 3).

The results in Table 3 indicate that the MVIM was able to provide perfect detection when faults were fully represented by the training sets (i.e., Cases #10, #11, #13, #16, #17, and #18), and that it produced better results than the Net in most of the cases. Specifically, the MVIM produced better results in twelve of the test cases, produced identical results in five cases, and was outperformed in only one case. Upon a casual inspection of the training sets that enabled MVIM to perform perfect detection, it can be observed that Tests #3 and #4 were included in all of them. This implies that the MVIM needed the parameters from these two tests to establish an effective pair of signatures for no-fault and fault cases. Note that without Test #3, the MVIM produced one undetected fault and one false alarm (Case #15), and without Test #4 it produced one undetected fault (Case #14). Note that the Net could not provide perfect detection even when trained with all of the five tests (Case #18).

Case #	Training Data Sets	Diagnostic Method	Undetected Faults	False Alarms	Total Test Errors
1	1	Net	4	0	4
		MVIM	1	3	4
2	5	Net	1	2	3
		MVIM	3	2	5
3	1,2	Net	4	0	4
		MVIM	2	2	4
4	1,3	Net	1	2	3
		MVIM	2	0	2
5	2,5	Net	3	2	5
		MVIM	3	2	5
6	3,4	Net	2	2	4
		MVIM	0	0	0
7	3,5	Net	0	3	3
		MVIM	1	0	1
8	4,5	Net	3	0	3
		MVIM	1	1	2
9	1,2,5	Net	1	2	3
		MVIM	1	2	3
10	1,3,4	Net	1	0	1
		MVIM	0	0	0
11	2,3,4	Net	2	0	2
		MVIM	0	0	0
12	2,3,5	Net	1	2	3
		MVIM	1	0	1
13	1,2,3,4	Net	2	0	2
		MVIM	0	0	0
14	1,2,3,5	Net	2	1	3
		MVIM	1	0	1
15	1,2,4,5	Net	1	1	2
		MVIM	1	1	2
16	1,3,4,5	Net	1	0	1
		MVIM	0	0	0
17	2,3,4,5	Net	2	0	2
		MVIM	0	0	0
18	1,2,3,4,5	Net	1	0	1
		MVIM	0	0	0

Table 3: Detection results obtained from MVIM and a multilayer neural net when trained with different data sets.

Fault Diagnosis: All of the fifty-four parameters obtained from the signal analyzer were used to train and test the MVIM in diagnosis. The configuration of the MVIM as applied to fault diagnosis of the OH-58A gearbox is illustrated in Fig. 6. As shown in this figure, two MVIMs were used for each accelerometer. One MVIM to perform detection (i.e., to determine whether a fault had occurred or not), and a diagnostic MVIM to isolate the fault. The detection MVIM contained only two columns to characterize the no-fault and fault signatures, whereas the diagnostic MVIM contained seven columns, one characterizing the no-fault signature and the other six representing the signatures of individual faults (see Table 2). Note that the two MVIMs can be perceived as filters with different resolutions. Test #3 and #4 contained most of the failure modes (i.e., four out of six). Therefore, the parameters from these two tests were used to train the MVIMs. Note that not all of the failure modes were included in training, so the test results were not expected to be perfect. For training the detection MVIMs, signal averaged parameters were excluded because it had already been established that the nineteen non-signal averaged parameters were adequate for detection. For training the diagnostic MVIMs, however, all of the fifty-four parameters were utilized. A maximum of fifty iterations were used for training both the detection and diagnostic MVIMs.

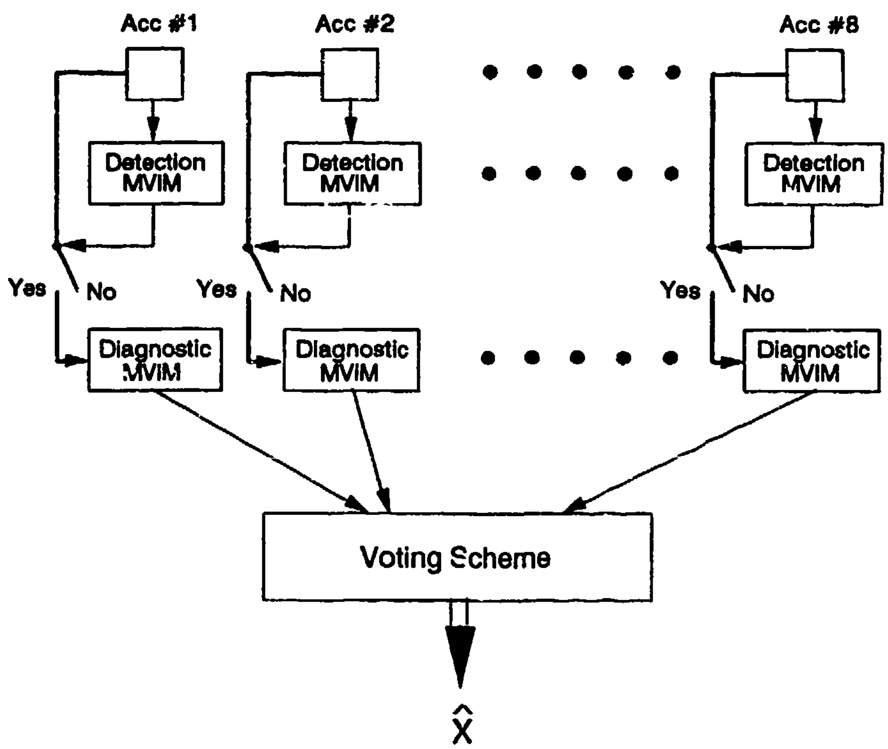

Figure 6: Configuration of the MVIM system as applied to the OH-58A main rotor transmission.

Individual MVIMs were considered converged when they produced perfect detection/diagnostics within the training set. The number of epochs for the convergence of the eight detection MVIMs were: 8, 5, 50, 37, 50, 15, 50, and 50 for accelerometers #1 to #8, respectively, whereas for the eight diagnostic MVIMs they were:

50, 1, 2, 2, 50, 50, 50, and 50. Based on the number of epochs used for individual MVIMs, it is clear that the detection MVIMs associated with accelerometers #3, #5, #7, and #8 did not achieve perfect detection within the training set. Similarly, the diagnostic MVIMs associated with accelerometers #1, #5, #6, #7, and #8 did not achieve perfect diagnosis within the training set.

The performance of the trained MVIMs were next evaluated for all of the five tests. For this purpose, the nineteen parameters from each of the eight accelerometers were first passed through the corresponding detection MVIM to reflect the occurrence of faults. Once the presence of a fault was indicated by a detection MVIM, the set of fifty-four parameters from that accelerometer was passed through the corresponding diagnostic MVIM to isolate the fault. Finally, the diagnostic results obtained from the eight diagnostic MVIMs were consolidated by a voting scheme. This voting scheme was designed based on assigning weights to individual fault signatures based on their speed of convergence in training, such that larger weights were assigned to those influence vectors which converged faster and vice versa. Zero weights were assigned to the influence vectors which did not converge during training; unity weights were assigned to those which converged within one epoch.

The diagnostic results obtained from the diagnostic system for all of the five tests are shown in Table 4, with the actual faults indicated inside parentheses. The results indicate that the MVIM system was able to produce perfect diagnostics for Tests #3 and #4, on which it was trained, and that it provided a correct diagnostic rate of 88% for all of the tests. Specifically, the results in Table 4 indicate that the MVIM system produced two false alarms (on day 4 of Test #1 and day 6 of Test #5), and five misdiagnoses (on days 5-8 of Test #1 and day 11 of Test #5). In addition, this system produced equal diagnostic certainty measures for the no-fault case (x_0) and sun gear failure (x_1) on day 10 of Test #5, and could only diagnose one of the faults on day 9 of Test #1 and on days 10 and 11 of Test #5. However, it should be noted that faults x_4 and x_5 were not included in training, so no fault signatures were estimated for them. The correct diagnostic rate of MVIM, with these two faults excluded would be over 95%, which is quite good considering that the MVIM system was trained on a small set of measurement-fault data with very few repetitions of each fault.

Summary of Results: An efficient fault detection/diagnostic system based on the MVIM method was applied to an OH-58A main rotor transmission gearbox. Detection results indicate that this system provided perfect detection when the full range of faults effects were included in training. Diagnostic results indicate that the system achieved a correct diagnostic rate of 95% despite very few repetitions of each fault.

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Day	Estimated Fault Status				
	Test #1	Test #2	Test #3	Test #4	Test #5
1	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)
2	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)
3	x_0 (x_0)	x_0 (x_0)	x_2 (x_2)	x_0 (x_0)	x_0 (x_0)
4	x_3 (x_0)	x_0 (x_0)	x_2 (x_2)	x_0 (x_0)	x_0 (x_0)
5	x_3 (x_4)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)
6	x_3 (x_4)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_6 (x_0)
7	x_3 (x_4)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_3 (x_3)
8	x_3 (x_4)	x_0 (x_0)	x_0 (x_0)	x_0 (x_0)	x_3 (x_3)
9	x_1 (x_4, x_1)	x_0 (x_0)	x_3 (x_3)	x_0 (x_0)	x_3 (x_3)
10			x_0 (x_0)	x_0 (x_0)	x_0, x_1 (x_3, x_1)
11			x_2 (x_2)	x_2 (x_2)	x_2, x_6 (x_3, x_1, x_5)
12			x_2 (x_2)	x_2 (x_2)	
13			x_6 (x_6)	x_0 (x_0)	
14				x_1 (x_1)	
15				x_1 (x_1)	

Table 4: Estimated faults for each day of the five tests. The actual faults (inside parenthesis) are also included for comparison. The x_i are the same as indicated in Table 2.

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13. ABSTRACT (*Maximum 200 words*)

The application of a newly developed diagnostic method to a helicopter gearbox is demonstrated. This method is a pattern classifier which uses a multi-valued influence matrix (MVIM) as its diagnostic model. The method benefits from a fast learning algorithm, based on error feedback, that enables it to estimate gearbox health from a small set of measurement-fault data. The MVIM method can also assess the diagnosability of the system and variability of the fault signatures as the basis to improve fault signatures. This method was tested on vibration signals reflecting various faults in an OH-58A main rotor transmission gearbox. The vibration signals were then digitized and processed by a vibration signal analyzer to enhance and extract various features of the vibration data. The parameters obtained from this analyzer were utilized to train and test the performance of the MVIM method in both detection and diagnosis. The results indicate that the MVIM method provided excellent detection results when the full range of faults effects on the measurements were included in training, and it had a correct diagnostic rate of 95% when the faults were included in training.

14. SUBJECT TERMS
Influence coefficients; Diagnostics; Failure analysis; Transmission (machine elements)

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